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GIS-based Land use/ Land cover Accuracy Assessment to identify dominant Species areas in Protected Savanna

Remote Sensing (RS) and Geographical Information System (GIS) are important tool used in image classification for sound forest management at local level. The factors which considered in classification, are spatial, radiometric and temporal resolution of satellite imagery, ground data, a precise classification process and expertise of the processes. The objective of this research was to classify land-use/land-cover (LULC) of the Rajiv Gandhi Orang National Park (RGONP) using RS and GIS techniques. Authors performed LULC classification through Iterative Self-Organizing Data Analysis (ISODATA) technique following accuracy assessment and Kappa statistics (K). The major LULC classified were Savanna (41%) and Woodland (30%). The dominant grass species found in RGONP are Saccharum sp., Imperata cylindrica, Arundo donax and Alpinia nigra. The study had an overall classification accuracy of 92.52% and kappa coefficient (K) of 0.89. The kappa coefficient is rated as almost accurate. Hence the classified image is found to be fit for further research. This study presents crucial information about protected area and can be useful for decision making in forest and wildlife management.

Key words: Savanna, GIS, Accuracy assessment, Kappa statistics, Threatened species

Nine Forest Class map with overall classification accuracy of 92.52% showed higher percentage of wet alluvial grassland than dry savanna.

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Introduction

Remote sensing is the art, science, and technology of observing and gathering information regarding objects on earth's surface, using satellite sensors, without coming in direct contact. GIS and RS can be used for collating, analyzing, updating and managing data in wildlife management or research projects (Zhang *et al.,* 2005). Earth observation satellites are indispensable for the estimation of land classification and land-cover monitoring (Asner *et al.,* 2002; Rodriguez-Galiano *et al.,* 2012). Satellite sensors use electromagnetic spectrum which depends on reflection and emission properties of the earth's surface, spectral features, texture and tone of optical data, which is important for the image classification (Lu and Weng, 2007). The mapping of wildlife habitats often arranges the basic area information for scientific studies and wildlife conservation, policy, planning and advisory work for area management (Belward *et al.,* 1990; Onojeghuo and Onojeghuo, 2015). To study and investigate relationship between fauna and flora, information on the distribution of vegetation type is very important (Akike and Samanta, 2016). Such mixtures exhibit multi-modal probability distributions. However, unsupervised techniques overcome the problem of distribution assumptions (Belward *et al.,* 1990).

The major challenge in land use or forest classification is to increase classification detail with satisfactory accuracy (Foody and Mathur, 2004). Bhuvan LULC classification for India is at National or State level but, for the purposes of intensive forest management, habitat characterization, and forest health monitoring, it is essential to obtain more detailed forest information. For national-scale forest assessment, the land cover maps

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can be used well but is insufficient for complex forest management at the local level, such as in Rajiv Gandhi Orang National Park (RGONP) savanna forests. However, detailed classification of savanna forests is difficult and not available due to the similarities in spectral reflectance, canopy structure, and spatial mixture of grass species. There is a clear need for a quality savanna map in RGONP to assess the habitat availability for threatened species. For example, a critically endangered species like Bengal Florican *Houbaropsis bengalensis* prefer *Imperata cylindrica* habitat (Birdlife International, 2017). A quality savanna cover map can assist in future research and conservation practices of these species. There are few forest cover maps containing forest types at national or state scales. The classification of savanna forests, however, does not separate *Imperata* sp. or *Saccharum* sp. areas despite the fact that *Saccharum* sp. is one of the most dominant species. Sarma in 2010 studied change detection on habitat attributes but did not consider species dominance in dry or wet savanna. For the land use and land cover mapping, the USGS proposed a recommendation of minimum accuracy of 85%. Our objective was to map a land cover and dominant grass species areas with better classification accuracy to meet various management practices.

Material and Methods

Study area

The Rajiv Gandhi Orang National Park (RGONP) occupies 78.80 km^2 area and is located in the north bank of Brahmaputra River (Lat: 26°29' to 26°40'N, Long: 92°16' to 92°27'E) in the Darrang and Sonitpur districts, Assam, India (Fig. 1). Area holds many threatened, endangered and endemic species such as, Greater One-horned Rhino *Rhinoceros unicornis*, Pygmy Hog *Sus salvanius*, Tiger *Panthera tigris*, Chinese Pangolin *Manis pentadactyla*, Bengal Florican *Houbaropsis bengalensis*, etc. (Mary *et al.*, 2013; Mane *et al.*, 2019). The vegetation in park can be broadly classified into five forest types (a) Eastern Himalayan Moist Deciduous, (b) Eastern Seasonal Swamp (c) Khair-Sisoo, (d) Eastern Wet Alluvial Grassland and (e) Plantations (Champion and Seth, 1968). More than 60% of the Park is under grasses such as *Imperata cylindrica, Saccharum* sp., *Cynodon dactylon, Arundo donax* (Hazarika and Saikia, 2012). Natural forest constitutes only 2.6%, while planted forest covers 13.6% of the Park area. Waterbodies and swamps constitute about 12% of the area (Birdlife International, 2020). In this study the authors aim to classify LULC with the following objectives. 1) Identify the land cover classes and their

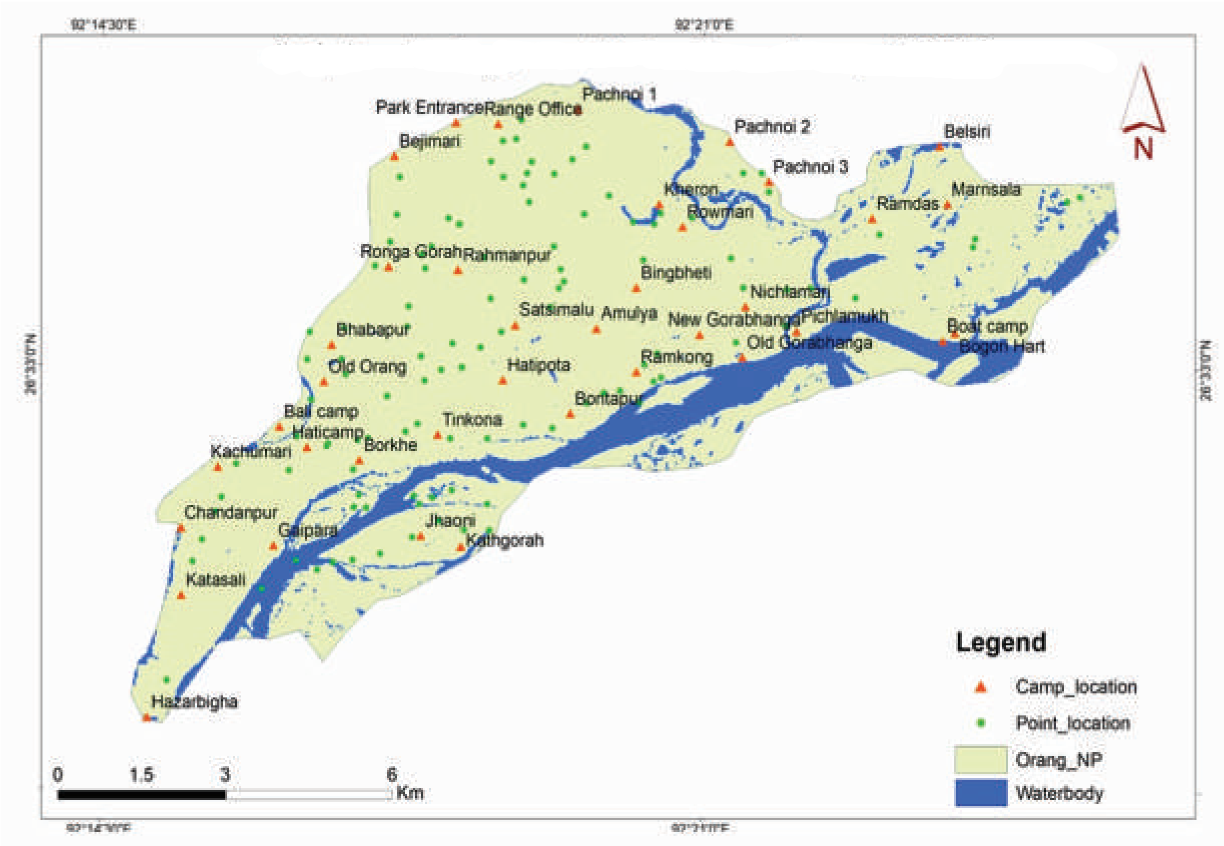

Fig. 1 : Study area showing ground data locations and camps at RGONP

proportion. 2) Estimate the proportion of dry and wet savanna land 3) comprehend the proportion and dominant species in savanna.

Methodology

Remote-sensing images acquired by Landsat-8 Operational Land Imager (OLI) sensor satellite were used to characterize vegetation in the RGONP. Landsat-8 OLI acquires images in eight spectral bands 1–7 and 9 at 30 m spatial resolution and in panchromatic band 8 at 15-m spatial resolution (Roy *et al.,* 2014). The study area was covered by a scene with worldwide reference system (WRS) path 136 and WRS row 42 in March, 2017. The atmospheric correction of the satellite imageries was performed to prevent changes due to atmospheric effects and can be interpreted as changes in the surface conditions (Vermote *et al.,* 2016). After atmospheric correction conversion of Digital Number (DN) values to the top-of-atmosphere (TOA) reflectance values was made using conversion coefficients in the metadata file (Roy *et al.,* 2014). Then chose the unsupervised method of classification for the land cover (Townshend and Justice, 1980). Further the authors adopted the Iterative Self-Organizing Data Analysis (ISODATA) clustering technique to distinguish the different forest vegetation cover types by evenly distributed class means (Kantakumar and Neelamsetti, 2015). Then it iteratively clusters the remaining pixels using minimum distance techniques (Melesse and Jordan, 2002). This process continues until the number of pixels in each class reaches maximum number of iterations (Kantakumar and Neelamsetti, 2015) (Fig. 2).

The ground location points were collected using Garmin eTrex 30 during February 2018– March 2019. The sampling plots were laid at minimum 15 meters apart (Total N= 115 locations). At each plot, a random (1 x 1 m) quadrates were laid 1m apart from each other at four directions (Sutherland, 2006). The grass cover (%), grass species (no.), bare ground (%) and dominant species (%) were recorded on each plot (Total plots N = 460). In this study, they were used as reference data for image classification. The authors grouped all plots data into Nine Forest Classes (NCF) based on (based on ≥50 % dominance) species combination of the plots. Grass and tree species were identified by using field guides and from field experts.

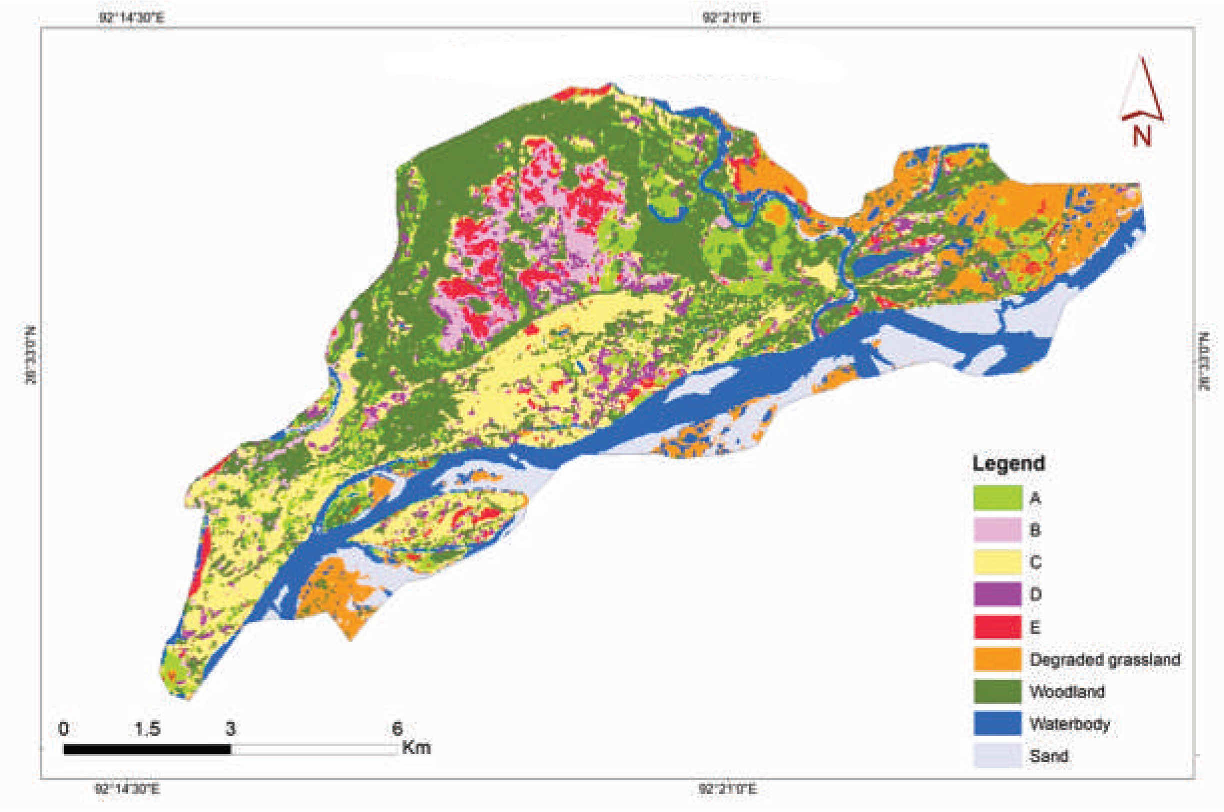

Fig. 2 : Land use Land cover of RGONP (vegetation classes A = *Imperata cylindrica, Saccharum ravennae* and *Alpinia nigra;* B = *Narenga porphyrocoma* and *Saccharum ravennae;* C = *Saccharum spontaneum, Saccharum ravennae, Arudo donax* and *Alpinia nigra;* D = *Imperata cylindrica* and *Vetiveria zizanoides;* E = *Impearata cylindrica, Saccharum* sp. and *Vetiveria zizanoides*; Degraded grassland; Woodland; Waterbody; Sand)

Details on distribution of continuous forest inventory plots to derive the land use classification at RGONP

A = 11 sampling points,

Dominant species: *Imperata cylendica* co-dominanted by *Saccharum ravennae* and *Alpinia nigra*.

Other/Associated species: *Mimosa invisa, Cynodon dactylon*

B = 9 sampling points

Dominant species: *Narenga porphyrocoma* co-dominated by*, Saccharum ravennae.*

Other/Associated species: *Leeacrispa, Chromolanea odorata, Ageratum conyzoides, Mimosa invisa.*

C = 17 sampling points

Dominant species*: Saccharum spontaneum* co-dominated by *Saccharum ravennae, Alpinia nigra, Arundo donax.*

Other/Associated species: *Desmodium gangeticum, Leersia hexandra Chromolanea odorata, Mikania micrantha.*

D = 14 sampling points

Dominant species: *Imperata cylendrica* co-dominanted by *Viteveria zizanoides.*

Other/Associated species: *Ageratum conyzoides, Mimosa pudica.*

E = 15 sampling points

Dominant species: *Narenga porphyrocoma* co-dominated by *Saccharum ravennae, Impearata cylendrica, Viteveria zizanoides.*

Other/Associated species: *Phragmites karka, Chromolanea odorata, Mimosa invisa, Neyraudia reynaudiana.*

Degraded grassland = 10 sampling points

Dominant species: Highly grazed/Barren land (Mix grasses of ~15cm height) over grazing by the domestic cattle from the fringe villages of the park.

Other/Associated species: Crysopogon aciculatus, Cynodon dactylon, (A major factor possibly an invasive species like *Mimosa invesa).*

Woodland = 20 sampling points, Natural and Plantation forest.

Other/Associated species: *Acacia catechu, Bombax ceiba, Sterculia villosa, Schima wallichi, Syzygium cumini, Syzygium fruticosum, Ziziphus mauritiana, A lebek, Alstonia scholaris, Anthocephalus cadamba, Samania saman, Schima wallichi, Bauhinia purpurea, Biscofia javanica, Ficus* sp., *Lagerstroemia speciose, Terminalia bellerica, Tectona grandis, Trewia nudiflora, Tona ciliate, Eucalyptus l.*

Waterbody= 12 sampling points, River, Rivulets, ponds, lakes*.*

Other/Associated species: *Hemarthria compressa, Pistia stratiotes, Eichhornia crassipes, Vallisneria spiralis, Hydrilla verticillata, Hymenachne pseudointerrupta.*

Sand = 7 sampling points, Sandbar, Sparse ground cover < 15% areas devoid of any vegetation concentrated around the riverbed of Brahmaputra.

Other/Associated species: covered with *Tamarix* and other grasses.

Accuracy assessment

Stratified random sampling was used for accuracy assessment on a per-category basis (Genderen and Lock, 1977). For each individual class, two measures of classification accuracy was used that are Users Accuracy (UA) and Producer's Accuracy (PA). The UA is a degree of commission error whereas PA corresponds to the omission error (Sader *et al.,* 1995). The performed map PA indicates the percentage accuracy with which a reference ground sample was classified. The UA indicates the percentage accuracy from the classified image which represents the cover type on the ground. An overall classification accuracy was made by dividing the total of the diagonal elements of a contingency table by the total for the whole table (Belward *et al.,* 1990). The accuracy assessment was made through a confusion matrix which contains information about actual and predicted classifications done by a classification system (Hasmadi *et al.,* 2009). Further, following Rwanga and Ndambuki (2017) authors calculated accuracy assessments including commission and omission error, sensitivity and specificity, positive and negative predictive power and Kappa statistics. Kappa analysis is a discrete multivariate technique used in accuracy assessment measures the difference between the actual agreement between reference data and classified data. It also measures the chance agreement between reference data and classified data (Lillesand and Kiefer, 1999).

Results and Discussion

The authors focused on and split the grassland into more detailed classes (A, B, C, D and E). The integration of image data and forest field data has made the forest cover map more realistic and objective than the use of image data alone. Both image and plot data were correctly geo-referred to make the spatial correction. The sample plots were laid extensively and randomly to make special representation and balance between the UA and PA. All these factors contributed to the development of the NFC map that is reasonably reliable with field data. The study area comprises 79.70 km^2. The total area under savanna was calculated 32.53 km^2 (41%), Woodland 23.59 km^2 (30%), Waterbody 10.39 km^2 (13%), Degraded grassland 5.95 km^2 (8%) and Sandbar 6.46 km^2 (8%) (Fig. 2).

The dominant composition of class C *(Saccharum spontaneum, Saccharum ravennae, Arudo donax* and *Alpinia nigra)* covering 43% of the savanna land at RGONP along riverside areas. Authors found very low area (11%) was covered with class E (*Impearata cylindrica, Saccharum* sp. and *Vetiveria zizanoides)* which is mainly present in core areas. The areas where the dominance of *Imperata cylindrica* in combination with *Saccharum ravennae* and *Alpinia nigra* (class A) was observed are comparatively high (22% of an area) than the areas where the dominance of *Imperata cylindrica* in combination with *Vetiveria zizanoides* (class D with 12% of an area) (Fig. 3). The *Narenga porphyrocoma* and *Saccharum ravennae* dominance (class B with 12% of an area) was seen in core areas. The area of wet alluvial grassland (21.23 km^2) was more (65%) than dry savanna (11.3 km^2, 35%) (Fig. 4). The degraded grassland areas covered 6.73 km^2. Authors found less area of dry savanna and degraded grassland mapped as 11.3 km^2 and 6.73 km^2, respectively compared to study by Sarma (2010) where area mapped was 21.23 km^2 and 23.59 km^2, respectively. The wet alluvial grassland and woodland areas found were comparatively similar to study done by Sarma (2010). The authors found *Narenga porphyrocoma* was dominant in the core areas and *Imperata cylindrical, Saccharum spontaneum* in the river side areas. They frequently sighted *Bengal florican* in *Imperata cylindrica* dominated areas of Rowmari, Nisilamari, Ramkong, Magurmari, Bejimari, Jhaoni, Satsimalu and Bontapur (Fig. 1). The Rowmari, Nisilamari, Magurmari and Satsimalu have high probability of *Mimosa invisa* whereas Magurmari, Rowmari and Rahmanpur has high probability of *Mikania micrantha.* The more sand areas *i.e.*, 6.46 km^2, than the area reported by Sarma (2010) for RGONP and Kaziranga National Park, possibly due to the change in course of Brahmaputra along with excessive siltation during monsoon.

The accuracies of the thematic maps were evaluated using confusion matrices for characterizing the performance of a classification technique (Rees, 1999). The ground truth locations have been used to assess the accuracy of the LULC image in which 3*3 majority analysis window is applied which removes misclassified and spatially singular pixels within homogeneous areas (Wagner *et al.,* 2011). The NFC map resulting from the classifications reached an overall classification accuracy= No. of correct points/total number of points = (99/107)*100 = 92.52%. The broad range of UA and PA indicates a severe confusion of class B, D and E with other land cover classes. Apart from class B, all classes showed more reliable with > 70% of user accuracy (Table 1). The forest class C and Degraded land had the highest accuracy on the average

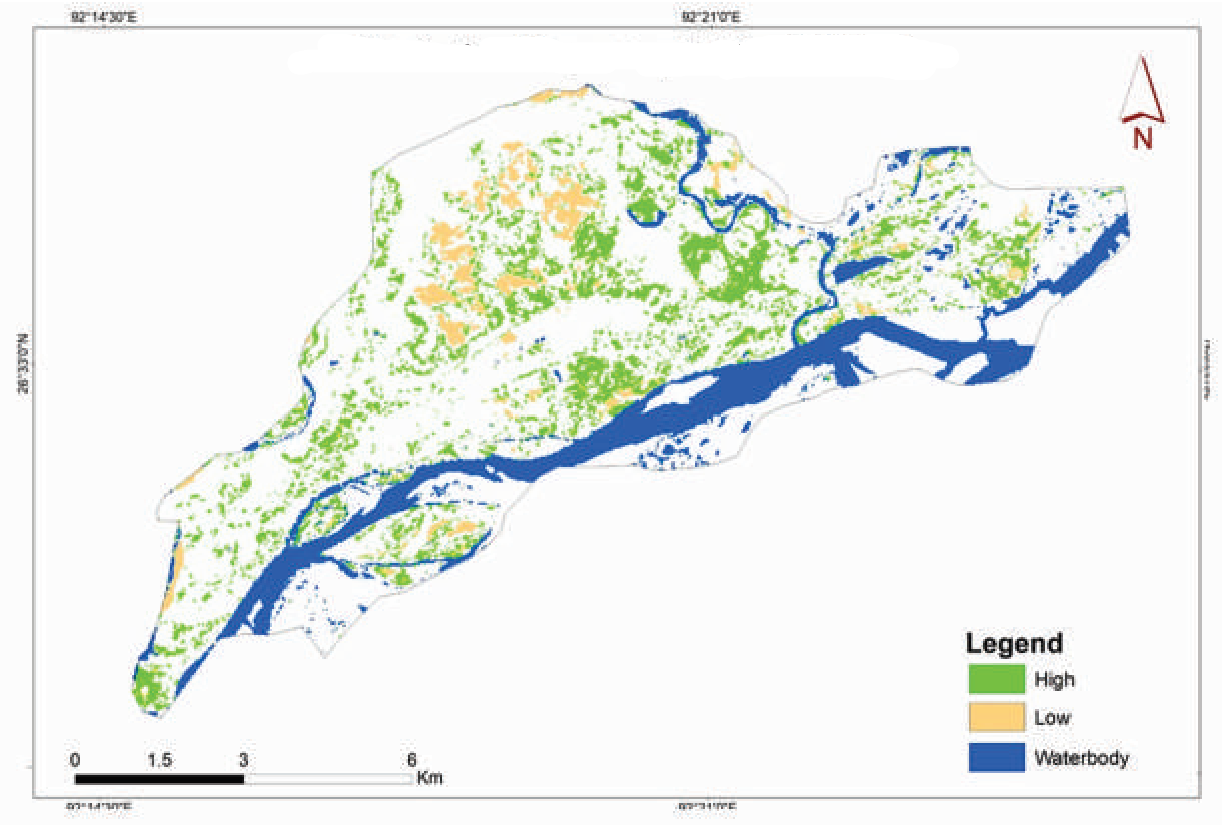

Fig. 3 : Distribution of *Imperata cylendrica* at RGONP

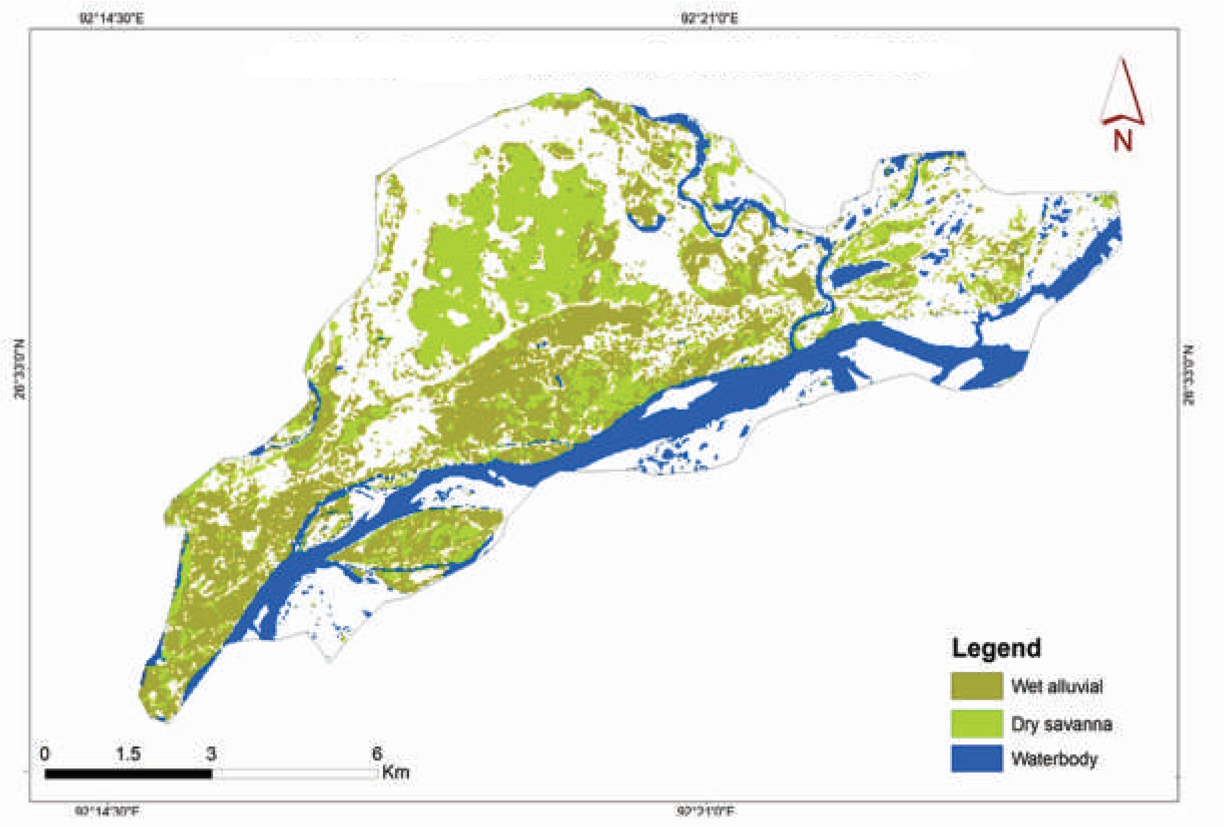

Fig. 4 : Distribution of dry savanna and wet alluvial at RGONP

of UA and PA, followed by class B, E, Woodland, Waterbody and Sandbar. The classification accuracy of class A and D were lower. The class E and Woodland forest had a rather low PA though its UA was relatively high (Table 1). The NFC map shows the dominant compositions of Savanna and Woodland, comprising 71% of the forested landscape in RGONP (Fig. 2). In this study an overall Kappa coefficient of 0.89 was obtained which is rated as almost perfect (Rwanga and Ndambuki, 2017).

Conclusion

The similarities in savanna community structure made its study and classification challenging. Kappa coefficient can allow us to test whether an individual land-cover map generated from remotely sensed data is significantly better than a map generated by randomly assigning labels to areas (Lunetta and Lyon, 2004). The change in forest type area is possibly due to natural succession, invasive species, burning practices, more defined park boundaries and management practices.

Table 1 : Category wise accuracy assessment and Kappa coefficient.

Land cover Classes	Parameters						Observed proportion of agreements (Po)	Expected proportion of agreement (Pe)	Kappa coefficient (K)
	Sensitivity	Specificity	Commission Error	Omission Error	User's Accuracy	Producer's Accuracy			
A	0.818	0.990	0.010	0.182	0.818	0.900	0.972	0.823	0.842
B	0.667	0.990	0.010	0.333	0.667	0.800	0.972	0.902	0.713
C	0.947	0.989	0.011	0.053	0.947	0.947	0.981	0.708	0.936
D	0.714	1.000	0.000	0.286	0.714	1.000	0.981	0.894	0.824
E	1.000	0.990	0.010	0.000	1.000	0.750	0.991	0.937	0.852
Degraded grassland	1.000	1.000	0.000	0.000	1.000	1.000	1.000	0.846	1.000
Woodland	1.000	0.962	0.038	0.000	1.000	0.906	0.972	0.592	0.931
Waterbody	0.933	1.000	0.000	0.067	0.933	1.000	0.991	0.766	0.960
Sand	1.000	0.990	0.010	0.000	1.000	0.889	0.991	0.854	0.936

Although most areas of semi-natural vegetation do not change substantially from year to year, certain management practices can have a significant effect. One among the vital anthropogenic factor is fire that stimulates the grass growth preferred by grazing ungulates. As per Belward *et al.,*1990 the areas burned during winter can get recovered in 3.5 years, but more recent burns do not appear on the image data, although they are obvious on the ground and needs to be studied. The main reason in decrease of grassland area in the park is possibly the impact of highly allelopathic and obnoxious invasive species like *Mimosa invisa* and *Mikania micrantha* which can tolerates a wide range of extreme conditions like severe drought or fire and which subdues the nearby vegetation (Wangmo *et al.,* 2018). Invasive species suppresses the growth of suitable foraging species of Greater One-horned Rhino and other ungulates (Medhi and Shah, 2014). The control of invasive species in RGONP is necessary for the wet alluvial and dry grassland, which can be managed by different measures suggested in earlier studies (Sarma, 2010). The uprooting practices of *Mimosa invisa* before formation of seeds (October and November) and before germinating sapling and seedlings (during April) needs to be monitored in different beats of park by the park authority. Similarly, water holding of artificial reservoirs/lakes at wet alluvial savanna needs to be checked during the dry season. The frequent monitoring of savanna is important for better understanding of its complex system and inhabiting wildlife. The class grouping was made in this study was on basis of dominance and proportion of species cover, which may vary with environmental changes. The regular monitoring of habitat in all protected areas should be done using geo-spatial tool for proper wildlife conservation and management practices.

संरक्षित सवाना में प्रमुख प्रजातियों के क्षेत्रों की पहचान करने के लिए जीआईएस-आधारित भूमि उपयोग/भूमि आवरण की सटीकता आंकलन

सनातोम्बा सिंह, अक्षया मोहन माने और रमेश के. गोगोई

सारांश

रिमोट सेंसिंग (आरएस) और भौगोलिक सूचना प्रणाली (जीआईएस) स्थानीय स्तर पर प्रभावी वन प्रबंधन के लिए छवि वर्गीकरण में उपयोग किए जाने वाले महत्वपूर्ण उपकरण हैं। वर्गीकरण में जिन कारकों पर विचार किया जाना चाहिए, वे हैं स्पेसियल, रेडियोमीट्रिक और उपग्रह इमेजरी का टेम्पोरल रिज़ॉल्यूशन, ग्राउंड डेटा, एक सटीक वर्गीकरण प्रक्रिया और प्रक्रियाओं की विशेषज्ञता। इस शोध का उद्देश्य आरएस और जीआईएस तकनीकों का उपयोग करके राजीव गांधी ओरंग नेशनल पार्क (आरजीओएनपी) के भूमि-उपयोग/भूमि-कवर (एलयूएलसी) को वर्गीकृत करना था। लेखकों ने इटरेटिवसेल्फ-ऑर्गेनाइजिंग डेटा एनालिसिस (आईएसओडीएटीए) तकनीक के माध्यम से एलयूएलसी टेक्नोलॉजी द्वारा सटीकता का आंकलन और कप्पा सांख्यिकी (के) का पालन किया। प्रमुख एलयूएलसी वर्गीकृत सवाना (41%) और वुडलैंड (30%) थे। आरजीओएनपी में पाई जाने वाली घास की प्रमुख प्रजातियाँ *सैकरम* प्रजाति, *इम्पेराटा सिलिंड्रिका*, *अरुंडो डोनाक्स* और *अल्पिनिया नाइग्रा* हैं। अध्ययनों में 92.52% की समग्र वर्गीकरण सटीकता और 0.89 का कप्पा मूल्य (के) था। कप्पा गुणांक को लगभग सटीक माना गया है। इसलिए वर्गीकृत छवि आगे के शोध के लिए उपयुक्त पाई गई। यह अध्ययन संरक्षित क्षेत्र के बारे में महत्वपूर्ण जानकारी प्रस्तुत करता है और वन और वन्यजीव प्रबंधन में निर्णय लेने के लिए उपयोगी हो सकता है।

References

Akike S. and Samanta S. (2016). Land use/land cover and forest canopy density monitoring of Wafi-Golpu project area, Papua New Guinea. *Journal of Geoscience and Environment Protection*, **4**(08): 1.

Asner G.P. and Heidebrecht K.B. (2002). Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: comparing multispectral and hyperspectral observations. *International Journal of Remote Sensing,* **23**(19): 3939-3958.

Belward A.S., Taylor J.C., Stuttard M.J., Bignal E., Mathews J. and Curtis D. (1990). An unsupervised approach to the classification of semi-natural vegetation from Landsat Thematic Mapper data. A pilot study on Islay. *Remote Sensing*, **11**(3): 429-445

BirdLife International (2017). Houbaropsis bengalensis (amended version of 2016 assessment). The IUCN Red List of Threatened Species 2017: e.T22692015A117249651.

BirdLife International (2020). Important Bird Areas factsheet: Orang National Park. Downloaded from http://www.birdlife.org on 16/05/2020.

Champion S.H. and Seth S.K. (1968). *A revised survey of the forest types of India.* A revised survey of the forest types of India. Govt. of India Press, New Delhi, p. 404.

Choudhury Manabendra Ray, Panna Deb, Hilloljyoti Singha, Biswajit Chakdar and MintuMedhi (2016). Predicting the probable distribution and threat of invasive Mimosa diplotrichaSuavalle and Mikania micrantha Kunth in a protected tropical grassland. *Ecological Engineering,* **97**: 23-31.

Foody G.M. and Mathur A. (2004). Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. *Remote Sensing of Environment*, **93**(1-2): 107-117.

Hasmadi M., Pakhriazad H.Z. and Shahrin M.F. (2009). Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. *Geografia: Malaysian Journal of Society and Space*, **5**(1): 1-10.

Hazarika B.C. and Saikia P.K. (2012). Food habit and feeding patterns of great Indian one-horned rhinoceros (Rhinoceros unicornis) in Rajiv Gandhi Orang National Park, Assam, India. ISRN *Zoology*, 2012.

https://forest.assam.gov.in/,Government of Assam environment & forest principal chief conservator of forest and head of forest force.

Jensen J.R. (2009). Remote sensing of the environment: An earth resource perspective 2/e. Pearson Education India. Upper Saddle River, New Jersey 07458, p1-541.

Kantakumar L.N. and Neelamsetti P. (2015). Multi-temporal land use classification using hybrid approach. *The Egyptian Journal of Remote Sensing and Space Science*, **18**(2): 289-295.

Lillesand T.M. and Kiffer R.W. (1999). Digital image processing in Remote sensing and image interpretation fourth edition, Willey, USA, 470-605.

Lunetta R.S.E. and Lyon J.G. (Eds.). (2004). *Remote sensing and GIS accuracy assessment*. CRC press.

Lu D. and Weng Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International journal of Remote sensing*, **28**(5): 823-870.

Mane A.M., Singh S., Khongsai N., Chakdar B., Mondal H., Gogoi M. and Jathar G.A. (2019). Identification of network of grassland corridors for conservation of threatened birds of Brahmaputra floodplains, India, *Bombay Natural History Society*, Mumbai, p103.

Mary P.P., Sinha R.R., Kumar A., Medhi M., Narayan G. and Deka P. (2013). Habitat characteristics of the Critically Endangered Pigmy Hog (*Porcula salvania*) of Manas National Park and Rajiv Gandhi Orang National Park in Assam, northeast India. In Knowledge Systems of Societies for Adaptation and Mitigation of Impacts of Climate Change, *Springer*, Berlin, Heidelberg, p405-421.

Medhi A. and Saha A.K. (2014). Land cover change and rhino habitat mapping of Kaziranga National Park, Assam. In Climate Change and Biodiversity (pp. 125-138). *Springer*, Tokyo.

Melesse A.M. and Jordan J.D. (2002). A comparison of fuzzy vs. augmented-ISODATA classification algorithms for cloud-shadow discrimination from Landsat images. *Photogrammetric Engineering and Remote Sensing*, **68**(9): 905-912.

Onojeghuo A.O. and Onojeghuo A.R. (2015). Dynamics of Forest Landscape Transition across Protected Areas in the Niger Delta from 1986 to 2014. *Journal of Geoscience and Environment Protection*, **3**(07): 1.

Rwanga S.S. and Ndambuki J.M. (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. *International Journal of Geosciences*, **8**(04): 611.

Rees G. and Rees W.G. (1999). *The remote sensing data book*. Cambridge university press.

Rodriguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., and Rigol-Sanchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. ISPRS *Journal of Photogrammetry and Remote Sensing*, **67**: 93-104.

Roy D.P., Wulder M.A., Loveland T.R., Woodcock C.E., Allen R.G., Anderson M.C. and Scambos T.A. (2014). Landsat-8: Science and prfoduct vision for terrestrial global change research. *Remote sensing of Environment*, **145**: 154-172.

Sader S.A., Ahl D. and Liou W.S. (1995). Accuracy of Landsat-TM and GIS rule-based methods for forest wetland classification in Maine. *Remote Sensing of Environment*, **53**(3): 133-144.

Sarma P.K. (2010). Habitat suitability for rhino rhinoceros unicornis and utilization pattern in Rajiv Gandhi Orang National Park of Assam. Ph.D.Thesis. North-Eastern Hill University, Shillong. 252pp.

Sutherland W.J. (Ed.). (2006). Ecological census techniques: a handbook. Cambridge university press, P 409.

Townshend J.R. and Justice C.O. (1980). Unsupervised classification of MSS Landsat data for mapping spatially complex vegetation. 1:2:105-120.

Vermote E., Justice C., Claverie M. and Franch B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sensing of Environment*, **185**: 46-56.

Van Genderen J.L. and Lock B.F. (1977). Testing land-use map accuracy. Photogrammetric Engineering and Remote Sensing, Salt Lake City, Utah 84119. 1-123.

Wagner P.D., Kumar S., Fiener P. and Schneider K. (2011). Hydrological modeling with SWAT in a monsoon-driven environment: experience from the Western Ghats, India. *Transactions of the ASABE*, **54**(5): 1783-1790.

Wangmo S., Lhendup S., Wangchuk D., Nidup T., Dorji T. and Wangchuk T. (2018). Ecology, Biodiversity and Approaches for Management of Specialthang Grassland in Royal Manas National Park. *Journal of Bhutan Ecological Society*, **3**-29-44.

Zhang He, C.Q., Li Y., Li X. and Shi P. (2005). Zoning grassland protection area using remote sensing and cellular automata modeling—a case study in Xilingol steppe grassland in northern China. *Journal of Arid Environments*, **63**(4): 814-826.

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